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Determination of Bus Station Locations under Emission and Social Cost Constraints

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Keywords
Public transportation, transit network planning, stochastic programming, sustainable behavior

Disciplines
Operational Research | Systems Engineering | Transportation Engineering

Comments
Determination of Bus Station Locations under Emission and Social Cost Constraints

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1. Introduction

There are many challenges in public transportation systems with regard to planning and operations management due to conflicting objectives of users and the service providers. For example, users may expect the most reliable and comfortable trip in a timely manner while service providers focus on building the most profitable system. Thus, an optimal system should be able to appropriately handle different decision preferences from users and service providers. Transit network planning involves all planning and operations management decisions that should be taken before the operation of a transportation system, and it is usually divided into subproblems at the tactical, strategic and operational levels [1]. Among various decision problems in transit network planning, the determination of vehicle types and stop stations is a common focus of strategic decisions for transit network planning [2]. Moreover, transportation network design is extremely sensitive to demand variations, so it is crucial to make long-term decisions considering demand fluctuations as well as seasonal variations. Furthermore, individuals have different perceptions on environmental sustainability; these different perceptions can influence passenger behavior in system use and transportation service performance (i.e., dissatisfaction levels). For instance, environmentally conscious people tend to walk much longer than others [3]. Therefore, an increase in walking time to a bus station may occur more frequently for customers who are aware of transportation emissions than those who are less aware of environmental problems. In this case, increasing walking distance will not lead to higher dissatisfaction levels for environmentally friendly customers in comparison to other customer types.

Although the relationship between sustainability beliefs and behaviors can have significant implications for utilization and service levels in transformation systems, extant studies that incorporate such concerns into transportation planning are limited. Most available studies focus on determining and analyzing factors impacting the passenger satisfaction of an existing system rather than using these factors for transportation planning. Friman and Fellesson [4] analyzed the relation between satisfaction level and public transport supply. Celik et al. [5] studied customer satisfaction level with transportation systems. They proposed a novel customer satisfaction evaluation model, which can determine the
criteria that needs improvement. To the best of our knowledge, the incorporation of uncertain demand, passenger perceptions on environmental sustainability, and service satisfaction levels has not been modeled to optimize transportation systems. In this regard, this study aims to determine a set of bus stations for an efficient public transportation system considering uncertain and dynamic demand, passenger perspective on environmental sustainability and weather effects. This research considers three cost aspects of transportation service management: operational, environmental, and social costs. One other significant contribution from the presented work is the identification and implementation of a method that can successfully steer the decision-makers away from system level over- or under-design.

2. Problem statement and formulation

The main goal of our work is to improve the quality of the public transit in order to increase its utilization while minimizing shortages. In this aspect, this study aims to determine an optimum set of bus stations and operating bus types considering weather conditions and different perceptions of passengers on environmental sustainability to minimize operational, environmental, and social costs of the system. The operational cost is determined based on the wage of a bus driver. The fuel consumption and emissions are included in the environmental cost. We consider the social aspects of the public transportation system and include social cost, which reflects the dissatisfaction level of passengers from the transportation service. Tyrinopoulos and Antoniou [6] stated that walking distance, bus fare, waiting time, and travel time by bus are key performance indicators to assess the performance of public transportation from the perspective of social needs. We include dissatisfaction levels of customers due to increasing walking distance and waiting time in the objective function as a social cost. Additionally, travel time by bus is incorporated as a constraint in the model.

We consider environmental sustainability beliefs of individuals that can affect their energy consumption [7]. Since environmentally conscious people are said to walk much longer than average [3], we expect that an environmentally conscious passenger’s dissatisfaction level from walking additional distance will be lower than those who are less aware of negative environmental concerns. Wang et al. [8] reported that an individual’s waiting tendency is correlated with their environmental protection behavior. Accordingly, if a bus provider chooses a small capacity bus when the demand is high, and if some passengers may not use the transportation system because of insufficient capacity, the dissatisfaction level for not being able to get on to the bus will be lower for environmentally conscious passengers than those who are less so. We deem that passengers who are less satisfied with the service will use the public transportation less. For instance, when the dissatisfaction level for walking additional distance or waiting is 0.9, we assume that the passenger will use the bus service once in every 10 cycles. We include the bus fare and the percentage of different passengers in terms of environmental sustainability for the determination of the social cost. In the model, weather effects have been considered by different dissatisfaction levels since the penalty of additional walking distance and waiting time will change based on weather conditions. To consider the random nature of the demand, the problem is formulated as a two-stage mixed integer stochastic programming model. The first stage is to determine a set of bus stations that will be constructed for a specific route among all potential bus stations. Given the results of the first stage, the second stage decides a bus type (e.g., small capacity vs. big capacity) that will operate in the route to minimize the total cost, which includes operational, environmental, and social costs. The parameters, variables and indices used in the model are listed below.

### Sets and indices

- $b : \{1, \ldots, B\}$ denotes bus types
- $s : \{1, \ldots, S\}$ denotes set of potential bus stations
- $i : \{1, \ldots, I\}$ denotes weather type
- $g : \{1, \ldots, G\}$ denotes passenger types based on their sustainability beliefs

### Variables

- $u_s$ : Number of passengers not served due to capacity shortage after leaving station $s$
- $w_s$ : Number of passengers not served due to not stopping after leaving station $s$
- $R_s$ : Number of available seats in bus heading to station $s$
- $T$ : Total riding time
- $x_{is} : \{1\}$, if bus stops at station $s$ in weather $i$
- $x_{is} : \{0\}$, otherwise
- $y_{ib} : \{1\}$, if bus type $b$ is selected in weather $i$
- $y_{ib} : \{0\}$, otherwise
- $\pi$ : Weight of selected bus type $b$

### Parameters

- $dw$ : Bus driver’s wage (USD/min)
- $D_s$ : Number of passengers delivered in station $s$
- $st$ : Stopping time in station
- $BM$ : Very big number
- $C_b$ : Capacity of bus type $b$
- $M_b$ : Weight of bus type $b$
The two-stage stochastic model is presented as follows:

\[
\begin{align*}
\text{Min } TC_i(x, \xi) &= dwT + \sum_{g=1}^{G} \sum_{s=1}^{S} \alpha_{g} w_{s} t p_{r g} + \sum_{g=1}^{G} \sum_{s=1}^{S} \gamma_{g} u_{s} t p_{r g} + EC \\
EC &= (C_f + C_o)(\omega \gamma \mu \{ac + gr \sin \theta + grCr \cos \theta\} \pi \nu T + 0.5Cd \sigma V^3 T)c + \omega y k N V T) \\
\pi &\leq M_b y_{ib}(\xi), \\
C_b - (1 - y_{ib}(\xi)) &\geq \pi, \\
R_s &= \sum_{b=1}^{B} C_b y_{ib}(\xi), \\
R_s &\leq R_{s-1} + x_{is-1}[D_{s-1} - P_{s-1}] + K_{is} B M, \\
R_s &\leq (1 - K_{is}) B M, \\
u_s &\geq P_s - D_s - \sum_{b=1}^{B} C_b y_{ib} - B M(1 - x_{is}). \\
u_s &\geq P_s - D_s - R_s - B M(1 - x_{is}), \\
u_s &\leq B M x_{is}, \\
w_s &\geq (1 - x_{is})[D_s + P_s], \\
\sum_{b=1}^{B} y_{ib}(\xi) &= 1. \\
RT + \sum_{s=1}^{S} x_{is} s t &= T, \\
T &\leq T_{\text{max}}, \\
\sum_{s=1}^{S} x_{is} &\geq 1, \\
u_s &\geq 0, \ w_s \geq 0, \ R_s \geq 0, \ K_s \geq 0, \ y_{ib}, x_{is} \in \{0, 1\}.
\end{align*}
\]

The objective function in Equation 1 minimizes the total cost \(TC_i(x, \xi)\), which includes the operational cost of buses, the social cost and the environmental cost. Constraint (2) calculates the environmental cost \(EC\) that consists of carbon emission and fuel cost based on the model developed by [9]. All parameters used in the environmental cost determination are adopted from this earlier study. Constraints (3-4) are related to vehicle type determination. Constraints (5-7) determine empty seats in the vehicle while heading to station \(s\). Constraint (8-10) are related to calculating service shortage due to bus capacity. Constraint (11) calculates the service shortage due to not stopping. Constraint (12) shows that only one type of vehicle can be selected for the route. Constraint (13) represents total riding time. Total riding time is restricted by an upper bound as shown in Constraint (14). Constraint (15) guarantees that the number of skipped bus stations does not exceed \(L\) which is a function of additional walking distance to the bus stations. Constraint (16) shows the positive and binary variables in the model.

3. Methods

Our model has two-stages, which includes determination of the optimal bus stations (\(x_{is}^*\)) and bus size (\(y_{ib}\)) for specific weather condition, \(i\). In the first stage, optimal bus stations are determined. Then, with input for the first stage decision variable and demand, the second stage optimizes the bus size. A key difficulty in solving stochastic problems is evaluating the objective function for numerous feasible scenarios and the possible realizations of the demand. The sample average approximation (SAA) is a simulation based method to solve stochastic problems by approximating true objective function using sampling of first stage decision variables [10]. A random sample size of \(N\) is generated (\(\xi_1, ..., \xi_n\)). Then, expectation of the total cost is approximated by solving the SAA problem, \(\min_{x \in X} \left\{ \frac{1}{N} \sum_{n=1}^{N} TC_i(x, \xi^n) \right\}\), where \(X\) represents locations of all possible bus stations, and \(x\) is a set of specific stations. Let 2\(z_i^*\) and \(\bar{x}_{is}^*\) be the predictors of the true objective function (\(z_i^*\)) and the first stage decision variable (\(x_{is}^*\)). As sample size increases 2\(z_i^*\) and \(\bar{x}_{is}^*\) converge to the optimal objective function and to the solution of the true problem. The steps of the SAA is presented below.

Step 1) For \(r = 1, ..., R\) generate samples each of size \(N\), i.e., (\(\xi_1^N, ..., \xi_n^N\)) and solve the SAA problem \(\min_{x \in X} \left\{ \frac{1}{N} \sum_{n=1}^{N} TC_i(x, \xi^n) \right\}\). Let 2\(z_i^R\) and \(\bar{x}_{is}^R\) be the optimal total cost and set of optimal bus stations for the \(r^{th}\) problem.
Step 2) Calculate $\bar{z}_i = (1/R) \sum_{r=1}^{R} \hat{z}_i^r$ as the lower bound on minimum average total cost and its variance, $\sigma_{\bar{z}_i}^2 = \frac{1}{R(R-1)} \sum_{r=1}^{R} (\hat{z}_i^r - \bar{z}_i)^2$.

Step 3) Find the minimum among $R$ solutions, $\bar{x}_i = \arg\min\{\bar{z}_i\}$. Fix $\bar{x}_i$ as the predictor of the optimal set of bus stations. Increase the sample size from $N$ to $N^*$ and solve the second stage problem $\hat{z}_{N}(\bar{x}_i) = \min \left\{ \sum_{n=1}^{N} TC_i(\bar{x}_i, \xi^n) \right\}$, which is determination of the bus size ($y_i$) under the fixed optimal set of bus stations ($\bar{x}_i$).

Step 4) Calculate the optimality gap $g_i = \hat{z}_{N}(\bar{x}_i) - \bar{z}_i$ and variance of the gap $\sigma_{\hat{z}_{N}(\bar{x}_i)}^2 = \sigma_{\bar{z}_i}^2 + \sigma_{\hat{z}_{N}(\bar{x}_i)}^2$, where $\sigma_{\hat{z}_{N}(\bar{x}_i)}^2 = \frac{1}{N(N-1)} \sum_{n=1}^{N} (TC_i(\bar{x}_i, \xi^n) - \bar{z}_i)^2$, and $\hat{z}_{N}(\bar{x}_i)$ is the average of the $N^*$ different total cost. If $g < \epsilon$, then stop the algorithm. Otherwise increase $R, N, N^*$ and go to Step 1.

4. Numerical Study

It is assumed that the transportation system provider wants to determine optimal bus stations that minimize the total operation, social and environmental costs for a particular route. There are 15 possible set of bus stations. The transportation system provider has two different bus types with different capacities. The big size bus has capacity of 25 passengers whereas the small one’s capacity is 15 passengers. The hourly wage of the bus driver is $18.25 [11]$ and the bus fare is $1.25 [12]$. We assume that the stopping time in each bus station is 0.5 min. The average speed of the bus is 40 km/h. The pickup and delivery demand for each station is randomly generated from a discrete uniform distribution and presented in Table 1.

<table>
<thead>
<tr>
<th>Demand</th>
<th>Possible Bus Stations</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P(s)$</td>
<td>U(8,12) U(2,6) U(3,7) U(5,8) U(6,9) U(4,7) U(1,4) U(3,6) U(4,8) U(3,7) U(2,5) U(1,4) U(1,5) U(0,3) U(0)</td>
</tr>
<tr>
<td>$D(s)$</td>
<td>0 U(0,1) U(1,3) U(1,3) U(0,3) U(2,5) U(0,3) U(1,3) U(1,5) U(0,3) U(0,4) U(5,8) U(2,5) U(3,6)</td>
</tr>
</tbody>
</table>

Concerning passengers’ environmental consciousness, we consider three different passenger types in the model. Passenger type 1 (P1) pays the highest attention to environmental sustainability. Passenger type 2 (P2) pays less attention in comparison to P1. Passenger type 3 (P3) represents individuals who do not focus on environmental issues.

We assume that each passenger type has different dissatisfaction levels for additional walking and wait duration. In the literature, it is stated that the average walking distance to a bus station is 400 m [13]. The average walking distance to each station is 200 m in our case study, and therefore, we use the dissatisfaction levels of three different passenger types for walking up to an additional 200 m. Dissatisfaction levels of different passengers for additional walking under various weather conditions $\alpha_{gi}$ are listed in Table 2. We assume that passengers who were not able to get on the bus because of the capacity limit will wait 10 minutes for the next bus. The dissatisfaction levels for waiting 10 minutes for varying weather conditions ($\gamma_{gi}$) are provided in Table 2. In the numerical case study, in lieu of a survey to collect dissatisfaction levels from different passengers for additional walking and waiting under weather conditions, we randomly generated dissatisfaction levels for each passenger. The dissatisfaction levels are biased with respect to passenger environmental consciousness; passenger type 1 has the lowest and passenger type 3 has the highest value.

<table>
<thead>
<tr>
<th>Passenger Type (g)</th>
<th>Summer (i=1)</th>
<th>Winter (i=2)</th>
<th>Summer (i=1)</th>
<th>Winter (i=2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>0.1</td>
<td>0.3</td>
<td>0.5</td>
<td>0.7</td>
</tr>
<tr>
<td>P2</td>
<td>0.3</td>
<td>0.5</td>
<td>0.9</td>
<td>1</td>
</tr>
<tr>
<td>P3</td>
<td>0.7</td>
<td>0.9</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

We solve the two-stage stochastic programming model with SAA parameters of $R=20$, $N=20$, $N^*=1000$. The model has 113 variables and 86 constraints. The algorithm is developed in GAMS 23.4 and solved by CPLEX. All numerical examples are run on an Intel(R) Core(TM)2 Quad 3GHz CPU PC with 8GB of memory. Given all parameters, we consider three different scenarios that include extreme cases for passenger transportation to specific zones to see how dissatisfaction levels for additional walking and waiting change the total cost and the set of bus stations for different weather conditions. In the first scenario, we assume that all the passengers are type 1, in the second scenario all passengers are equally distributed across all three types, and in the last scenario, all passengers are of type 3. The total
costs in 95% confidence interval (CI) and optimal set of bus stations for each scenario and weather type are presented in Table 3. As the penalty for additional walking and waiting for winter is high, the number of optimal bus stations and the total cost increases comparing to summer.

Table 3: Optimal bus stations and total cost in 95% CI

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Total cost Summer (i=1)</th>
<th>Set of bus stations Summer (i=1)</th>
<th>Total cost Winter (i=2)</th>
<th>Set of bus stations Winter (i=2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1</td>
<td>[41.76-42.55]</td>
<td>1,4,6,9,13,14</td>
<td>[51.37-52.37]</td>
<td>1,3,4,6,7,9,12,13,14,15</td>
</tr>
<tr>
<td>Scenario 2</td>
<td>[53.62-54.81]</td>
<td>1,3,4,6,7,8,10,13,14,15</td>
<td>[58.00-59.82]</td>
<td>1,4,6,7,8,9,10,11,12,13,14,15</td>
</tr>
<tr>
<td>Scenario 3</td>
<td>[62.53-65.11]</td>
<td>1,3,4,5,6,8,9,10,11,12,13,14,15</td>
<td>[64.33-66.99]</td>
<td>1,2,3,4,5,6,7,8,9,10,12,13,14,15</td>
</tr>
</tbody>
</table>

In the second stage of the numerical study, we further investigate how the distribution of the passenger types affects operational, social and environmental costs as well as the number of bus stations for a particular $\alpha_{gl} = [1, 0.1, 2, 0.3, 3, 0.7]$ and $\gamma_{gl} = [1, 0.5, 2, 0.9, 3, 1]$ when weather effect is not included. Figure 1 presents the change on average operational, social and environmental costs for each scenario. In Scenario 1, when all the passengers are type 1 (P1:1, P2:0, P3:0), the average operational cost, social cost and environmental costs are: $8.8$, $5.94$ and $27.41$, respectively. As the distribution of the type 2 and type 3 increases, all the costs increase as expected. Table 4 provides the optimal number of bus stations and the 95% confidence interval for each cost.

Figure 1: Change on operational, social and environmental cost

Table 4: Optimal bus stations and 95% CI for the costs

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Number of bus stations</th>
<th>Operational cost</th>
<th>95% Confidence Interval for costs</th>
<th>Social cost</th>
<th>Environmental cost</th>
<th>Total cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Scenario 1</td>
<td>6</td>
<td>[8.74-8.86]</td>
<td>[5.88-6.00]</td>
<td>[9.63-9.81]</td>
<td>[41.89-42.41]</td>
<td></td>
</tr>
<tr>
<td>Scenario 2</td>
<td>10</td>
<td>[9.20-9.32]</td>
<td>[8.72-8.84]</td>
<td>[28.79-28.91]</td>
<td>[46.78-47.18]</td>
<td></td>
</tr>
<tr>
<td>Scenario 5</td>
<td>12</td>
<td>[9.51-9.63]</td>
<td>[16.42-16.54]</td>
<td>[29.75-29.87]</td>
<td>[54.92-56.80]</td>
<td></td>
</tr>
<tr>
<td>Scenario 6</td>
<td>12</td>
<td>[9.51-9.63]</td>
<td>[19.27-19.39]</td>
<td>[29.75-29.87]</td>
<td>[57.61-59.81]</td>
<td></td>
</tr>
</tbody>
</table>

In the third stage of the numerical study, the proposed model and the traditional solution approach are compared in terms of total cost and social cost using two sample $t$-test in order to prove the benefit of the proposed model. In the proposed model, we determine the number of bus stations so as to minimize the operational, social and environmental costs. However, in the traditional approach, we consider operational and environmental costs in the objective function but not the social cost. The total number of bus stations, distribution of passenger types and the penalties are kept the same in both cases. Since the number of total bus stations is equal across the two models, we have the same operational and environmental costs. However, there is a hidden social cost in the traditional solution approach due to not considering customer dissatisfaction. This hidden cost is calculated by the average demand in the skipped stations multiplied by the penalty of additional walking for each passenger and bus fare. The two sample $t$-test showed that the proposed model reduces the total cost ($t=2.18$, $df=36$, $p=0.036$) and social cost ($t=3.46$, $df=36$, $p=0.002$) significantly. Figure 2(a) and 2(b) show the average and 95% confidence interval of social and the total cost for the proposed model and the traditional solution approach respectively. The proposed model provides $6$ of the total cost advantage by considering dissatisfaction levels of different individuals per each cycle on the average.
5. Conclusions
This study develops a two-stage stochastic programming model in order to minimize the total cost for running a bus system. The first stage of the model decides the optimal set of bus stations while the second stage determines the bus size for a particular bus route. The novelty of the study is in the consideration of the individuals’ environmental consciousness and related behavior and perceptions. We integrated dissatisfaction levels of different individuals of varying levels of environmental consciousness for additional walking and waiting. Moreover, the model also takes into account the fuel consumption for an environmentally sustainable transportation system. In the numerical study, we investigate how the dissatisfaction levels of the individuals and their distribution in a particular zone change the set of bus stations and the operational, social and environmental costs. With regards to the numerical study, an increase in the percentage of passengers whose behaviors do not reflect environmental awareness increases both the total cost and the number of bus stations. Furthermore, in order to present the cost advantage of our model, we compared our proposed model with the traditional approach. The proposed model satisfies $6 cost advantage in each cycle. By assuming 15 cycles in a day, the model achieves $90 cost advantage in a day and $2700 cost advantage in a month. We will extend our study to find a robust set of bus stations regardless of weather conditions.

References